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Evaluating Community Emergency Department Crowding: The Community ED Overcrowding Scale (CEDOCS) study.

Running header-CEDOCS tool for ED overcrowding

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Keywords-overcrowding, ED administration, metrics/scales

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Objectives The goals of this study were to: (1) Identify valid variables that correlate with Emergency Department ED crowding and (2) Determine a model that could be used to accurate reflect the degree of ED crowding.

Methods: A site sampling form was applied to convenience sampling of 13 community hospitals in California between 4/6/2011 and 5/1/2011. The outcome variable was average perception of crowding by the ED physician and charge nurse on a 100mm visual analogue scale. We focused on 20 candidate predictor variables that represented counts and times in the ED that were collected every four hours. A prediction model was developed using multivariable linear regression to determine the measures that predicted ED crowding. A parsimonious model was developed to allow for a clinical useful tool that that explained a significant amount of variability predicted by the full ED crowding model.

Results: A total of 2,006 datasets were collected for each of the participating hospitals. A total of 1,628 time entries for the hospitals were included in the study. Hospital EDs had censuses ranging from 18,000 to 98,000. Full evaluation was completed on 1489 datasets. Twenty variables were considered for the full model with 7 removed due to multi-collinearity. The remaining 13 variables constituted the full model and explained 50.5% of the variability in the outcome variable. Five predictors were found to represent 92% of the variability represented by the full model.

Conclusions: Five variables were highly correlated with community ED crowding and could be used to model the full set of all variables in explaining ED crowding.

Keywords-overcrowding, ED administration, metrics/scales

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1. INTRODUCTION

1.1 BACKGROUND: One approach to the study of ED crowding is to develop a scoring tool or metric that would reflect conditions in the ED. By utilizing a metric, hospitals can develop mechanisms to systematically address high ED volumes thus preventing bad patient outcomes. In a review of crowding scoring tools, Hwang et al[1] only found 4 with operational definitions with a multi-dimensional analysis. The READI (real-time Emergency Analysis of Demand indicators) score, proposed by Reeder et al[2], used capacity and demand value but did not show good agreement with providers assessment of crowding. Bernstein et al[3] developed the EDWIN (Emergency Department Work Index) in 2003. It used triage ESI triage categories and numerical values about ED capacity. It correlated excellently with the nurse/physician assessment of crowding. The NEDOCS scale, developed by Weiss et al[4-9], did a complete statistical analysis of input, throughput and output variables related to the ED and found a model consisting of 6 variables that reflected ED nurse/physician assessment of crowding with excellent results. The EDCS score developed by Asplin et al.[10] found significant correlation between the score and ED length of stay, mean boarding time, ambulance diversion and left without being seen rates. These metrics have been shown to be helpful in evaluating the degree of crowding. None of these specifically addressed community EDs.

In their review of the literature, Hwang[1] states that the EDWIN and NEDOCS demonstrated the most evidence of validity in association with clinician opinion of crowding, diversions and left without being seen rates. NEDOCS and EDWIN were found to be comparable in their prediction of crowding however the NEDOCS score showed better statistical significance and was easier to obtain. [6] The techniques used to develop these two scales can help us to develop future scoring system.

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1.2 **IMPORTANCE**: Research on a scoring tool specifically to measure crowding in community hospitals has not been done yet. The NEDOCS scale has value in reflecting the opinions of staff on crowding, but it was only validated in large academic major trauma centers. There is the need to develop a scoring tool that takes into account patient count and time interval variables in the community setting.

1.3 GOALS OF THIS INVESTIGATION: We set out to develop a new scale applying the methods used to develop NEDOCS.[4;8] To help answer the question of what variables are important in reflecting community ED crowding, an assessment site sampling tool was developed using state and national Emergency Medicine experts. It included variables used by the NEDOCS calculator and others that were important to other state expert groups. The purpose of this study was to correlate variables in determining crowding in different sized community EDs. The goals of this study were to: (1) Identify valid variables that correlate with ED crowding and (2) Determine a model that can be used in the future to accurate reflect the degree of ED crowding among community hospitals. The hypotheses were that we could identify valid variables correlated with crowding and that a reduced model with 6 or less variables could represent a significant amount of the variability noted in a crowding variable.

2. METHODS

2.1 Site sampling form development.

A site sampling form was developed including predictor variables based on literature review and input from an expert committee devoted to addressing ED crowding issues. Table 1 lists all predictor variables (and their operational definitions) that were collected during data collection. Using this new site sampling form, data was collected at a sampling of 13 California community hospitals. A total of 216 site sampling forms were obtained for each of

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the participating hospitals every 4 hours for a 3-week study period. The characteristics of the hospitals included in the study group are shown in Table 2. Table 3 compares the study sample of hospitals to the overall makeup of CHA member hospitals that have Emergency Departments.

Data collection

The site sampling form and all variables were explained to each site collector and questions were answered prior to initiation of that site's data collection. Site collectors were trained by one of the authors using previous studies and a glossary of terms. During the data gathering phase, data was collected every four hours between 4/6/11 and 5/1/11. All hospital information was collected prospectively by onsite personnel and transmitted to a data aggregator at CHA under a memorandum of understanding (MOU) that allowed for research analysis and publication of the de-identified data. This study accessed and analyzed that de-identified database. It was approved by our University human research review committee.

2.2 Study Setting and population.

Using this new site sampling form, data was collected at a sampling of 13 California community hospitals. (Table 2) The demographic range of hospitals included in the study group is shown in Table 2. Table 3 shows how the included sample reflects the overall makeup of CHA member hospitals that have Emergency Departments. A total of 216 site sampling forms were obtained for each of the participating hospitals. Observation datasets were removed from the final analysis if they were missing 10 or more predictors of if the outcome variable was missing.

2.3 Outcomes

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The outcome variable was the average perception of crowding by the ED physician and charge nurse on a 100mm visual analogue scale that ranged from not busy to significantly overcrowded. The VAS was anchored by dividing it into six segments with each, in turn, labeled with "Not busy", "Busy", "Extremely busy, not overcrowded," "Crowded," "Severely crowded," and "Dangerously crowded." Therefore anything over the 50mm point on the line was within one of the areas labeled as crowded.

2.4 Data Analysis

Site specific data were available for >90% of the hospitals that were included in the analysis. All analyses were conducted using the R package (http://www.r-project.org). The "rms" (http://biostat.mc.vanderbilt.edu/wiki/Main/RmS) package in R was used to impute missing data on variables and to fit the prediction model. This package also incorporates methods for relaxing linearity assumptions by using restricted cubic splines. Data characterizing individual hospitals and individual variables are described using means, standard deviations and confidence intervals). Independent and outcome variables were compared using a Spearman correlation coefficient. Because all variables were obtained in >90% of cases, no missing values procedure was used.

A multivariable linear regression model for crowding using CEDOCS as the outcome variable was generated. The model was fitted using the following 13 candidate predictors. For all ordinal and continuous variables, non-linearity was assessed using restricted cubic splines and removed if the P value was greater than a conservative 0.20 value. Since no a priori information was available concerning interactive effects, none were specified for the full model. Finally, a reduced parsimonious model that would be more user-friendly was used for estimating crowding. The reduced model was developed based on a model that included predictors that accounted for

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at least 90% of the variability of the full model or when a predictor variable explained at least 2% of the variability of the outcome. The method used was based on a stepdown approach for simplifying a prognostic model.[11] A website was developed for obtaining predictions from the reduced model.

A high degree of multi-collinearity was determined based on either having extreme pairwise correlation (correlation coefficient at least 0.707 which corresponds to an R-square of 0.50) between two candidate predictors or a large variance inflation factor (VIF at least 4.0).[12] VIF is defined as 1/(1-R-squared) where R-squared is the proportion of variability explained by the remaining candidate predictors.

3. RESULTS

3.1GENERAL RESULTS

Table 2 shows the differences and similarities among the included hospitals. The comparison to CHA member hospitals is illustrated in Table 3. A total of 2006 sampling forms were collected among the participating hospitals with each hospital collecting 126 timed datasets. Of the 13 included hospitals, 1628 times were sampled and were included in the study. Hospitals ranged in size from 18 to 65 thousand annual ED visits, 64 to 643 licensed hospital beds, 7 to 49 ED beds and between 4 and 19 thousand admissions per year. The hospitals were community hospitals that were designated as base hospitals. Median hospital occupancy ranged from 60% to 113%. The only significant difference between the 13 included hospitals and the entire CHA dataset was that our sample included more trauma centers as shown in table 3.

A total of 1628 observation datasets were recorded. Of these, 114 had at least 10 missing predictors leaving 1514 observation datasets. Another 25 observation datasets were removed because of missing outcome, which left us with 1489 total datasets for further evaluations. Table 4 shows the correlation between each individual time and count variable collected and the outcome variable (crowding) for determining the reduced model. The most highly correlated variables with the outcome

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were "Longest time patient is waiting to be seen in the ED" (0.51), "Number of patients in waiting room" (0.50), and "Number of patients in the ED"(0.57)

3.2 REDUCED MODEL - CEDOCS

The outcome variable was first evaluated to establish its reliability and validity. The correlation coefficient representing the agreement between physicians and nurses on the VAS was 0.83 overall (range of 0.57 to 0.97) across the entire group of hospital, indicating good interrater reliability and a highly consistent rating system.

Twenty variables, listed in Table 1 were considered for the full model. Of the 20 candidate predictor variables available for modeling, 7 were not retained due to a high degree of multi-collinearity. Five variables removed due to high VIFs were "Number of patients in the ED" (variable D.3, VIF=10), "Number of nurses with direct care responsibilities" (variable D.6, VIF=10), "Number of hospital beds" (variable A.3, VIF=6), and "Number of admitted and transfer patients in the ED" (variable D.6, VIF=5). Three other measures were also removed due to their extreme correlation with other measures. "Longest time patient is waiting to be seen in the ED" (variable C.2) was removed due to its strong correlation with "Number of patients in waiting room" (varable D.1, correlation= 0.87), "Number of ED beds" (variable A.2)due to correlation with "Number of hospital beds" (variable A.3,correlation =0.85), and "Longest time psychiatric patient is waiting in ED" (variable C.1)due to its correlation with "Number of psych patients in the ED" (variable D5, correlation= 0.79). The reduced model was then determined based on 2 fixed variables, 2 descriptor variables, 1 time variable, 6 count variables and 2 ratio variables. These 13 variables are shown in Table 5 as explained in the next paragraph.

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The original independent variables are illustrated in Table 5, which is ordered by significance of the variables in the model with those of most significance at the bottom of the table. The five variables in the shaded portion of table 5 were chosen for the reduced model, representing 92% of the variability of the full model (0.463/0.501=92%).

In the next step, linearity of the variables was examined. ED visits per year was found to be the only non-linear variable thus leading to a cubic spline analysis. The best fit for the nonlinearity of the variable was with 3-degrees of freedom illustrated in figure 2. Interestingly, the contribution of ED visits/ year to the crowding measure increased to about 40,000 ED visits per year then dropped until about 50,000 patient visits per year before leveling off. When this was taken into account in the reduced model, the coefficient of determination increased to 0.474 representing 95% (0.474/0.501) of the variability in the full model.

The formula used to calculate the CEDOCS score is the following:

(1)	{-30.39+
(2)	3.00*A +0.53*B+1.16*C+20.66*D+
(3)	0.00126* E -
(4)	(1.11e-12)*pmax(E-18811,0)^3
(5)	8.23e-12*pmax(E-43012,0)^3 -
(6)	8.20e-12*pmax(E-49466,0)^3 +
(7)	1.08e-12*pmax(E-67273,0)^3 }

A= No. of critical care patients
B= Longest time for an admitted patient waiting in the ED since admission
C= No. of patients in the waiting room
D= No. of ED patients to # ED bed ratio
E= ER visits/year

Lines 3 to 7 of this formula calculate the nonlinear variable, ED visits/yr. The Pmax function means that if the subtraction term is at least 0, then that resulting term to the third power is multiplied times the coefficient, otherwise the entire line is 0. For example, an ED with 46,000 patient visits/yr, lines 4 and 5 would have values and lines 6 and 7 would be zero. The equation would look like the following:

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(1)	{-30.39+
(2)	3.00*A +0.53*B+1.16*C+20.66*D+
(3)	0.00126* 46000 -
(4)	(1.11e-12)*(27189*^3)
(5)	(8.23e-12)*(2988)^3 }

The final crude and adjusted models of overcrowding are displayed in Table 6 with effect sizes. The effects are for the specified comparisons. For example, the 3.1 effect for critical care ED patients is the effect on outcome when comparing critical care ED patients of 0 to 1. . In the table changing the variable based on the comparison shown caused a change in the predicted outcome variable shown as effect. For example, a change in Critical Care ED patients from 0 to 1 increased the value of the CEDOCS outcome score by 3 (on the 100 point scale). Because the predictor ED visits per year was not linear, it can be seen that changing sizes of the ED has varying effects on the CEDOCS score.

3.3 CEDOCS vs NEDOCS

Unlike NEDOCS, the calculations for CEDOCS were based on a scale of 0 to 100, so doubling the CEDOCS score gives values in the same range as NEDOCS. Mean outcome variable (visual analogue score) results for this dataset were 29 ±15 with a range from 0 to 100. CEDOCS score results for the dataset also had a mean of 29 ±15, also with a range of 0 to 100. In contrast, mean NEDOCS scores calculated for this dataset were 74 ± 50 with a range of 0 to 200. When comparing CEDOCS and NEDOCS to the outcome variable, the coefficient of determination (R squared) was 47% for CEDOCS and 39% for NEDOCS indicating that CEDOCS is about a 20% improvement over NEDOCS in this set of hospitals. In comparing the new reduced model (CEDOCS) to the previously validated NEDOCS scale, we found that three of the variables were the same: (1) Number of ED beds, (2) ED patients to ED bed ratio, and (3) Longest wait time for admitted patients. Four new variables were found to be important in the development of the new CEDOCS score:

(1) "Number of hospital beds" was replaced with "Number of ED visits/yr,"

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(2) Number of respirators," was replaced with "Critical care ED patients,"

(3) "Total admits in the ED" is replaced with "Number of waiting room patients", and

(4) Waiting room wait time was removed.

Figure 2 illustrates the website that we have developed to allow for easy access to the CEDOCS algorithm (http://hsc.unm.edu/emermed/cedocs2012d.shtm) .

4. DISCUSSION

Even after more than 20 years of research in ED crowding, a precise definition of ED crowding eludes us.[13-19] While much of the literature is focused on the effects of crowding, the metrics by which we measure the problem are still in flux. Each study uses the author's favorite approach to evaluate whether crowding exists, the extent of the crowding and its effect on patient care.[20-28] However, without a constant metric, we cannot compare among these studies. We therefore set out many years ago to develop a metric to reflect ED crowding using expert opinion of degree of crowding as our standard. The metric, the NEDOCS score, has held up over time as the best score in comparison to the myriad of other possible scoring systems because it was conceived with face validity based on all considered variables, was independently developed using a purely statistical approach to the data and was easy to apply and use. If a hospital matches the inclusion criteria of the NEDOCS study, then that scale is the best we have been able to find.[7;8] However, the primary criticism of NEDOCS has been its external validity.[1] While the scale has functioned well and proven itself in a test of time in academic settings, this criticism still applies. In the present study we worked to address this criticism by developing a scale based on diverse community hospitals that were significantly different from the original NEDOCS hospital set. The NEDOCS study was based on large academic EDs and thus has validity issues when applying the score to a more diverse range of community based

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hospitals. We found a coefficient of variability(R squared) of 0.39 for the NEDOCS and of 0.47 for the CEDOCS on this dataset. It can be seen that the NEDOCS was about 83% as effective in this environment (0.39/0.47=0.83). While not an extremely large difference, CEDOCS is about 20% better in reflecting the outcome variable in the community hospitals included in this dataset.

Comparing the two scoring systems illustrates some of the differences in the ED inclusion criteria. In the NEDOCS derivation, hospitals were all >40,000 patient visits a year and academic institutions. We now present a scale based on hospitals with censuses as low as 18,000 patient visits a year with all of them being non-academic sites. The CEDOCS scale is composed of community based EDs and has better applicability to this type of institution.

Another difference from the NEDOCS study was the percent of the time that EDs were crowded. In the NEDOCS study, because of the nature of the hospital sites, some sites were crowded as much as 73% of the time. In this study, we found that approximately 30% of the time was considered crowded by the ED charge nurse and physician. This is probably more reflective of normal community hospital operation.

We looked specifically at ED occupancy which has been suggested as a good marker of ED crowding and found that it, by itself, was not representative enough of the complex nature of ED crowding to suffice as a measure of that variable. While it is by far the simplest, correlation with the crowding outcome variable was 0.6, less than the correlation for either NEDOCS (r=0.62) or the CEDOCS (r=0.67). All other indicators of crowding fell short of either of these scoring systems.

Finally crowding research needs to continue to examine the outcomes due to crowding, as diverse as the number of medical errors, bacterial contamination, pain management, patient satisfaction, time to treatment or patients leaving without being seen.[20;21;23;26;27;29-35]

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Further study should focus on defining levels at which the metrics that we have developed could be used to implement policies that would improve patient care and decrease the identified problems associated with crowding as an issue. It appears that crowding will be around for quite some time. The economic model of supply and demand that would suggest that we need more ED and hospital beds is in collision with the medical insurance based model that continues to cut the expenses and levels of care at the expense of our patients. We will continue to struggle with this problem and must continue work on methods to restrict the impact that crowding has on good patient care.

5. LIMITATIONS AND FUTURE DIRECTIONS

As described above, the external validity of the study is limited by the specific hospital types that were included in the study. Whether a hospital chooses NEDOCS, CEDOCS or another metric of crowding should depend on how that hospital ED matches with the inclusion group that was studied.

There are other variables that were not considered in the dataset that could be related to crowding. The lesson learned from the NEDOCS study is that, with changes over time, variables arise and will continue to arise that are not yet part of ED management but could become integral to the crowding issue. For instance, the variable "tweeners", which represents a "subtriage" area between the waiting room and a bed in the ED, did not exist at the time of the NEDOCS study. In addition, "psych patients awaiting admission" were not a problem in the particular hospitals in the original NEDOCS study but have become more of a recent problem in community based hospitals. As new approaches to management of patient throughput are created, new variables will continue to arise that we could not take into account at the present point in time.

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Another limitation was the definitions used in understanding the study variables. Hospitals were provided with a "dictionary" of terms and were careful about ensuring full understanding and compliance with the study dataset collection. Some of the variables still could be misunderstood during the data collection phase.

6. CONCLUSIONS

For the included hospitals, multiple variables were highly correlated with ED crowding. Six of these variables taken together can accurately predict ED crowding as determined by the nurse and physician in charge. Hospitals can use this scale to determine cutoffs that can drive administrative decisions to improve patient throughput in the ED.

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Table 1: Candidate Predictor Variables Preselected for a crowding model

A. Fixed Variables	Operational definitions
A.1. ED visits/year	No. ED visits/year as presented to State Health Planning Office
A.2. Number of ED beds	No. ED beds as presented to State Health Planning Office
A.3. Number of hospital beds	No. hospital beds as presented to State Health Planning Office
A.4. Percent Occupancy of inpatient routine beds (recorded 1/day)	Once daily record of # of total beds in use compared to # of hospital beds (generally recorded at midnight)
B. Descriptors	
B.1. Day of the week	Day of the week
B.2. Time of the day	Time of the day
C. Time variables (nearest 1/4 hrs-)	
C.1. Longest time psychiatric patient is waiting in ED	Present time minus decision-to-admit time for the longest waiting psych pt.
C.2. Longest time patient is waiting to be seen in the ED	Present time minus ED presentation time for the longest waiting pt.
C.3. Longest time an admitted patient is still waiting in the ED	Present time minus decision-to-admit time for any non-psych ED pt
D. Count Variables	
D.1. Number of patients in waiting room	Simple count of patients in the waiting room
D.2. Number of patients in the triage area("Tweeners")	Simple count of patients in a triage area
D.3. Number of patients in the ED	All patients in beds plus those doubled up or in hallways if they are being seen there.
D.4. Number of admitted and transfer patients in the ED	Count of all admits and non-psych transfer patients in the ED
D.5. Number of psych patients in the ED	Count of all psych patients in the ED
D.6. Number of nurses with direct care responsibilities	Count of nurses directly assigned to pt care duties
D.7. Total number of licensed nurses in the ED	Count of nurses with direct pt care duties plus administrative nursing staff.
D.8. Number of admitted critical care patients in the ED**	Count of any pt admitted to a critical care area of the hospital and still in the ED
D.9. Number of patients on ventilators in the ED	Count of ventilators in use in the ED for critically ill patients.
E. Ratio Variables	
E.1. ED patients to ED bed ratio*	Ratio of D.3 to A.2
E.2. Admitted patients to hospital bed ratio.	Ratio of D.4 to A.3

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Table 2: Information on fixed variables by hospitals.*

Hospit al ID	Annua l ER Visits (per	License d Beds (OSHP D, 2009***	License d ED Beds	Acute Inpatient Beds Routinely Used	Annual Admissio ns (OSHPD, 2009***)	Traum a Center (level)	Base Hospit al	Percent Occupancy Median (IQR)**
1	30	64	26	62	5	-	Yes	98(92,104)
2	56	320	27	200	16	2	Yes	94(90,98)
3	66	290	28	290	11	2	No	113(109,11
4	19	100	7	100	5	-	Yes	74(67,79)
5	41	460	36	420	18	-	Yes	76(72,77)
6	47	220	36	220	12	2	Yes	82(76,85)
7	30	170	12	120	10	2	No	78(74,82)
8	46	350	34	300	18	2	Yes	75(74,79)
9	44	270	20	140	12	-	Yes	68(64,71)
10	43	200	19	110	9	-	Yes	131(69,151)
11	43	640	49	400	18	2	Yes	72(68,78)
12	50	380	36	320	17	-	Yes	92(83,93)
13	67	310	34	310	16	2	Yes	63(53,71)

* Three hospitals removed due to incomplete outcomes.
**IQR=Inter-quartile range
***OSHPD- Office of Statewide Health Planning and Development

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Table 3: Comparison of Study Sample with 350 California Hospital Association(CHA) hospitals with emergency departments.

	Study sample Mean (SD)	All CHA hospitals Mean (SD)	Mean or Proportion Difference (95% CI)
N	13	344	
Annual ED visits	45(14)	36(26)	9(-5,23)
Licensed beds	290(153)	245(178)	45(-53,143)
Licensed ED beds	28(11)	22(15)	6(0.04,12)
Annual admissions(per 1,000)	13(5)	10(8)	3(-1,7)
Trauma centers	54%(7/13)	21% (72/344)	33%(5,59)
Base hospitals	85%(11/13)	90%(308/344)	-5%(-36,8)

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Table 4: Association between Crowding and Time and Count Predictor variables (N=1498 datasets)

	Median (IQR)	Range	Correlation with Crowding	P value
Time Variables				
C.1.Longest time psychiatric patient is waiting in ED (Hours)	0 (0,6)	**0-110**	- 0.09	0.001
C.2.Longest time patient is waiting to be seen in the ED (Hours)	0.25(0,1)	**0-27**	0.51	0.001
C.3.Longest time an admitted patient is still waiting in the ED (Hours)	5 (2,8)	**0-34**	0.27	<0.001
Count Variables				
D.1.Number of patients in waiting room (N)	1(0,4)	**0-37**	0.50	<0.001
D.2. Tweeners (N)	0(0,3)	**0-10**	0.24	<0.001
D.3.Number of patients in the ED (N)	21 (12,30)	**0-67**	0.57	<0.001
D.4.Number of admitted and transfer patients in the ED (N)	3 (1,5)	**0-41**	0.39	<0.001
D.5.Number of psych patients in the ED (N)	0(0,1)	**0-27**	0.12	<0.001
D.6. Number of nurses with direct care responsibilities (N)	7 (5,10)	**0-33**	0.30	<0.001
D.7.Total number of licensed nurses in the ED (N)	10(7,13)	**0-29**	0.20	<0.001
D.8.Number of admitted critical care patients in the ED (N)	0(0,1)	**0-10**	0.28	<0.001
D.9.Number of patients on ventilators in the ED (N)	0(0,0)	**0-6**	0.11	<0.001

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Table 5: Results of step-down variable selection for all 13 candidate predictor variables in a full model fit (R2=50.2%). The model presents predictors in decreasing order of importance to the prediction of crowding. Bottom five predictors explained over 90% of the full model that include 13 predictors. ****

	Variability Explained	Drop in Variability Explained	P-Value
B.1. Day of the week	50.2% (full) model)	100%	0.63
D.9. Number of patients on ventilators in the ED	50.1% (remove Day of week)	99.8%	0.73
E.2. Admitted patients to hospital bed ratio	50.1%	99.8%	0.70
D.5. Number of psych patients in the ED	50.1%	99.8%	0.62
A.4. Percent Occupancy of inpatient routine beds	50.0%	99.6%	0.19
D.2. Number of patients in the triage area("Tweeners”)	49.7%	99.0%	0.004
B.2. Time of the day	49.2%	98.0%	<0.001
D.6. Number of nurses with direct care responsibilities	48.4%	96.4%	<0.001
D.8. Number of admitted critical care patients in the ED**	**47.4%**	**94.4%**	**<0.001**
C.3. Longest time an admitted patient is still waiting in the ED ED visits per year	**46.3%**	**92.2%**	**<0.001**
D.1. Number of patients in waiting room	**44.4%**	**88.4%**	**<0.001**
A.1. ED visits/year	**40.9%**	**81.5%**	**<0.001**
E.1. ED patients to ED bed ratio*	**36.1%**	**71.9%**	**<0.001**

*ED patient to ED bed ratio explains 36% of the crowding variability and 72% (36%/50.1%) of the full model with 13 predictors.

**Critical care ED patients explains 47% of the crowding variability.

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Table 6. Crude (unadjusted) and Adjusted Results of Multivariable Regression Analysis for Predicting Crowding

		Full Multivariable Model			Reduced 5-variable Model		
Candidate Predictor	Comparison	Effect	95% CI	P	Effect	95% CI	p
A.1. ED visits/year				<0.0001			<0.0001
	20k to 30k	10.5	6.9,14.0		10.9	8.6,13.2	
	30k to 40k	3.8	1.9,5.7		3.6	2.4,4.7	
	40k to 50k	-6.4	-8.9,-3.8		-7.6	-9.7,-5.5	
	50k to 60k	-2.5	-3.8,-1.2		-3.1	-4.2,-2.0	
A.4. Percent Occupancy of inpatient routine beds	70% vs 90%	-3.4	-5.7,-1.2	0.01			
B.1. Day of the week	Monday vs Sunday	-1.63	-4.5,1.3	0.63			
B.2. Time of the day				0.0007			
	9AM vs 1AM	2.7	-0.1,5.5				
	9AM vs 5AM	3.8	1.0,6.5				
	9AM vs 1PM	0.8	-2.5,3.3				
	9AM vs 5PM	-0.3	-3.8,3.3				
	9AM vs 9PM	-3.2	-6.8,0.5				
C.3. Longest time an admitted patient is still waiting in the ED	2 vs 8 hr	3.0	2.0,4.0	<0.0001	3.1	2.2,4.1	<0.0001
D.1. No. of patients in waiting room	0 vs 4	5.0	4.0,6.0	<0.0001	4.6	3.6,5.5	<0.0001
D.2. No. of patients in the triage area	0 vs 3	-3.6	-5.9,-1.4	0.003			
D.5. No. of psych patients in the ED	0 vs 1	0.5	-0.4,1.4	0.27			
D.6. No. of nurses with direct care responsibilities	7 vs 13	4.6	1.7,7.6	<0.0001			
D.8. No. of admitted critical care patients in the ED*	0 vs 1	3.0	1.8,4.2	<0.0001	3.1	2.1,4.2	<0.0001
D.9. No. of patients on ventilators in the ED	0 vs 1	-0.4	-3.1,2.3	0.77			
E.1. ED patients to ED bed ratio	50% vs 100%	11.1	9.7,12.6	<0.0001	10.3	9.2,11.4	<0.0001
E.2. Admitted patients to hospital bed ratio	1% vs 2%	0.4	-0.2,-.9	0.23			

No.=Number; Full Multivariable Model R-squared=50.2%; Reduced parsimonious model R-squared=47.4%.

*The effects are for the specified comparisons. For example, the 3.1 effect for critical care ED patients is the effect on outcome when comparing critical care ED patients of 0 to 1.

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Figure 1: Relationship between CEDOCS Crowding score (outcome) with ED visits per year.

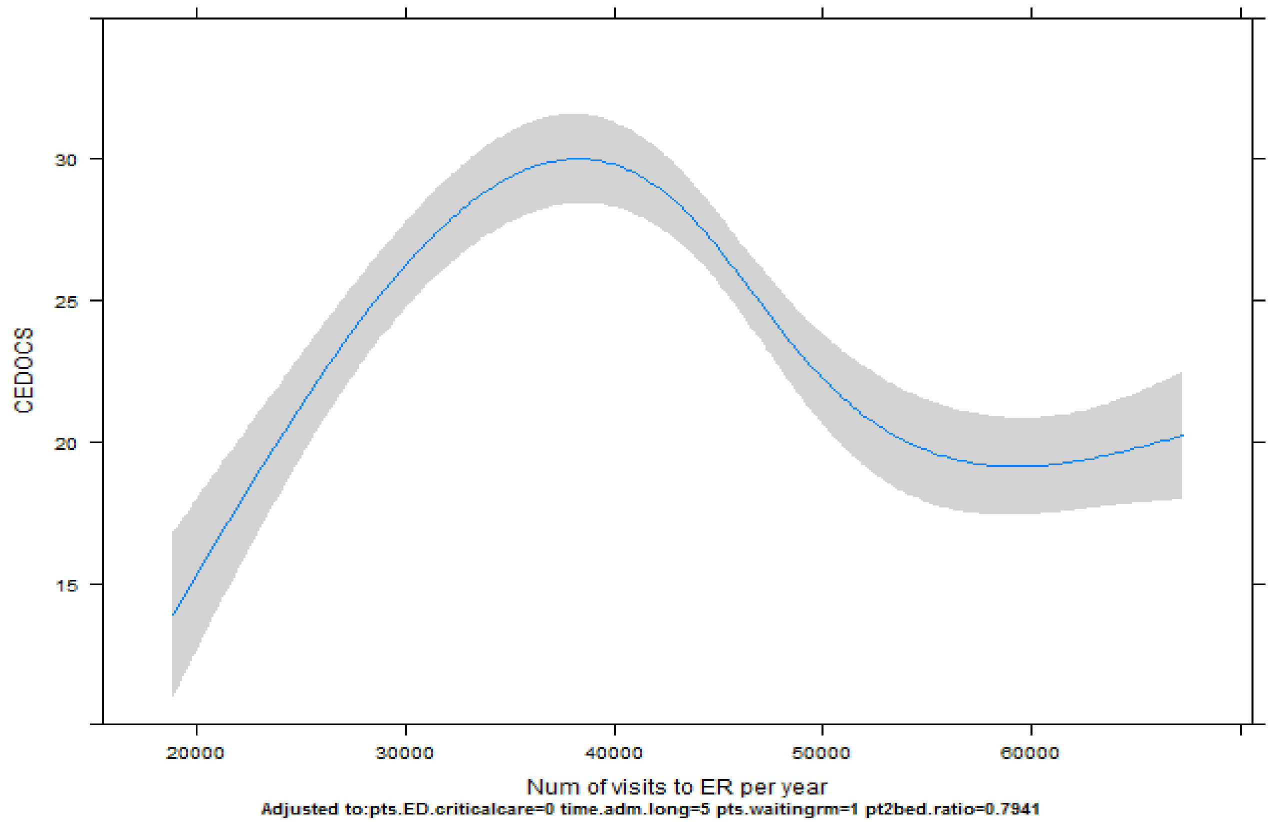

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Figure 2: Website for calculating CEDOCS